Independent Component Analysis (ICA) of EEG, Concepts and Methods
Part 1 – Concepts

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Outline

• EEG and the cocktail party problem
• Linear superposition of EEG sources
• Typical EEG sources
• Back-projection of separated sources
• Dependency and subspaces
  – ICA separates dependent subspaces from other activity
  – Back-projection of subspaces
  – Dynamic components
• Non-stationarity
Cocktail Party Problem

- EEG analysis as separation of *multiple simultaneously active* brain sources, similar to microphones recording and multiple simultaneous speakers, e.g. at a cocktail party

- ICA originally proposed for separation of multiple independent audio signals (early ‘90s)
- Scott Makeig proposed ICA for EEG source separation (1996), in collaboration with Tony Bell and Terry Sejnowski at Salk
A source is essentially defined by the pattern of electrical potential that it projects onto the electrodes (by volume conduction)
EEG Sources

- Stationary source activity (local and stable) fluctuates, or oscillates, around zero, causing alternation of positive and negative potentials at the scalp.
EEG of one source

- EEG electrodes record the source activity weighted by different values depending on electrode location relative to the source.
EEG of three sources

- EEG records multiple sources that are simultaneously active
EEG Data

- Raw EEG records large number of simultaneously active sources
- From physics, we know that EEG at one instant is simply the sum of all source activity at that instant
Linear Superposition

• Let the EEG data be represented by the vector of time varying electrode potentials $x(t)$, and let the source activities be $s_i(t), i = 1, \ldots, n$

• Let the scalp maps (patterns of potential) be represented by vectors $a_i, i = 1, \ldots, n$

• The EEG data is the sum:

$$x(t) = s_1(t) a_1 + s_2(t) a_2 + \ldots + s_n(t) a_n$$
Decomposition of EEG

• Given the EEG data, $X$, we would like to decompose it into source scalp maps multiplied by source activity, $X = AS$, with $A$ and $S$ unknown.
Typical ICA scalp maps
Typical ICA sources – alpha
Typical ICA sources – theta
Back-projection

- Separated sources can be “back-projected” to the scalp to examine contribution of individual sources at electrodes
Pairwise mutual information

- Pairwise mutual information (PMI):
  \[ [M]_{ij} = I(x_i; x_j) = h(x_i) + h(x_j) - h(x_i, x_j) \]
  PMI is a measure of dependence between sources

- Comparison of PMI for original data and ICA
Dependent subspaces

- Residual dependence structure can be seen using Pairwise Mutual Information (PMI) plot.
- Block diagonalizing this matrix (heuristically), we see blocks corresponding to dependent subspaces of components.
Alpha dependence

- Below four alpha components are shown
- This alpha activity exhibits dependence and coherence
- There is actually an alpha “subspace”
- Is alpha a “distributed dynamic” phenomenon?
Alpha Dynamic Component

- Alpha component maps:
- Subspace can be extracted along with dynamics and played as a movie:
Muscle dependence

• Muscle components tend to be active at the same time

• Activity is uncorrelated, but nevertheless dependent

• Activity is non-Gaussian, marginal histograms are “sparse”
Variance Dependence and ICA

• We can show that minimizing the total mutual information will separate variance dependent sources

• PMI can be used to analyze dependence structure after ICA has been performed
Non-stationarity

- Typical EEG recordings are non-stationary—sources and distributions differ over course of recording.
- We use a mixture model approach to learn multiple ICA models
Conclusion

• Problem of separating EEG sources is similar to the “cocktail party problem” of separating simultaneous audio sources.

• Individual sources, e.g. contributing to ERPs, can be separated and back-projected to examine activity at the scalp electrodes, or map can be “localized” to determine source location in brain.

• Sources may exhibit residual dependency, but ICA usually separates a “subspace” from other sources.

• Data may be non-stationary, but a mixture of ICA models can be used to represent different time periods with different ICA models.

• Part 2 after lunch ...